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Going beyond perfect rationality: drought risk, economic choices and the influence of social networks

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Abstract Theoretical and experimental studies from psychological and behavioral sciences show that heuristics and social networks play an important role in decision-making under risk. The goal of this paper is to investigate the effects of empirical social networks and different behavioral rules on farmers' irrigation adoption under drought risk and its impacts on several macroeconomic indicators such as the rate of adaptation, water demand and regional agricultural income. We present an application

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of a spatial economic ABM which is able to simulate the effect of droughts on crop production, farm income and farm decision-making. The agents' population is parameterized using survey data, including data on social networks. Four experiments are conducted combining two climate scenarios with two behavioral scenarios (maximizers vs. heuristic-based agents). The results show that the adoption process follows a different path in the scenario with heuristic-based farmers. The adoption of irrigation is slower in the short run due to reliance on information from social networks and farmers' uncertainty regarding drought events. This results in agricultural income loss and a lower water demand in the short run compared to the scenario with maximizing agents.

Mathematics Subject Classification Q150 Drought; Irrigation; Farm · D010 Bounded rationality · D030 Heuristic Agent based model

1 Introduction

Patterns of regional development are largely driven by choices of economic actors. A dynamic pathway toward the prosperity or impoverishment of a region is shaped by many individual economic choices amplified through social interactions and subject to institutional and geographical environments (Boshuizen et al. 2009; Batten 2001). Moreover, the future economic welfare of regions worldwide relies on specific manifestations of climate change, most of which require adaptation to their adverse consequences (IPCC 2014). When studying climate adaptation, the uncertainties about climate change, individual behavior and economic consequences are large. Therefore, an effective policy formulation in which private and public adaptation initiatives are aligned is a challenging task. To be successful, one needs to explore the consequences of adaptive choices under risk as our investment decisions today shape spatial patterns of development and economic welfare of regions in the future. Analytical, statistical, equilibrium and computational simulation models serve as tools to support policy makers at the local, regional or country level.

Models employed in the economic discipline often rely on the assumptions of a rational representative economic agent maximizing its goal function under conditions of perfect information and in the absence of biases or information asymmetries. This allows for elegant solutions yielding a unique equilibrium. Yet, there is an increasing trend in economic literature to question the appropriateness and consequences of these assumptions (Arthur 1999; Tesfatsion 2002; Farmer and Foley 2009), especially if interactions with the natural system are considered (Liu et al. 2007). Economic models are being extended to account for out-of-equilibrium dynamics (Arthur 2006), agent heterogeneity (Kirman 2006), bounded rationality (Simon 1997) and interactions between agents (Axtell 2005). In the context of climate change, probabilistic risks and uncertainty need to be explicitly considered, which load even more weight on the level of complexity expected from economic models. Traditionally, they rely on expected utility theory (EUT) to capture decisions under uncertainty. EUT assumes that individual decision-makers quantify uncertainties on all possible states of the world, value and weight them on their probability of occurrence and choose the alternative with the highest expected utility (Von Neumann and Morgenstern 1944). Yet, there is growing evidence from the psychological and behavioral literature that people are boundedly rational and that intuitive processes or heuristics and information from social networks are utilized to make decisions under risk.

Specifically, empirical and experimental studies show that risk perception, experiential factors, feelings of dread or worry, perceived self-efficacy and perceived behavioral control bias individual decision-making (Tversky and Kahneman 1973; Rogers 1975; Maddux and Rogers 1983; Slovic 1987; Ajzen 2002; Slovic et al. 2004, 2007). Prospect theory, for example, shows that individuals are biased in their risk judgement because they weigh uncertain negative consequences much more heavily than uncertain gains (Kahneman and Tversky 1979; Tversky and Kahneman 1992). Moreover, many economic choices are subject to an influence from social networks (Jackson 2010). The social amplification of risk framework states that individual risk perceptions are susceptible to social norms through interactions within social networks (Kasperson et al. 1988). Social interaction, disaster risk experience and risk mitigating behavior are processes underlying individual and social learning and may change preferences and decision over time.

Quantitative models, which are capable of incorporating these behavioral aspects to explore the cumulative economic consequences of climate risk and compare them to aggregated outcomes based on traditional economic assumptions, are in demand. Ideally, such a model should also be spatially explicit as many research and policy questions in the field of regional sciences deal with the spatial development of regions. Yet, it is a real challenge to construct an economic model that is capable of integrating insights from behavioral studies and economic choices with social networks while still operating in a heterogeneous spatial environment. Agent-based computational economics (ACE) has proven successful in modelling various economic phenomena while going beyond a representative maximizing agent with perfect information.

ACE is the study of economic processes, modelled as evolving systems of heterogeneous interacting agents with the use of computers and simulation techniques (Tesfatsion and Judd 2006). Economic agents in agent-based models (ABMs) interact with each other and the environment according to particular rules giving rise to emergent macrophenomena (Farmer and Foley 2009). ABMs have been applied to study various economic phenomena, for example financial markets (LeBaron 2001; Feng et al. 2012), commodity markets (Gode and Sunder 1993; Graubner et al. 2011; Kirman and Vriend 2001), energy markets (Bunn and Oliveira 2003; Sun and Tesfatsion 2007), land markets (Chen et al. 2011; Filatova et al. 2011; Magliocca et al. 2011; Filatova 2014; Parker 2014), systems of cities (Mansury and Gulyás 2007) as well as agricultural economics questions (Balmann 1997; Berger 2001; Happe et al. 2006; Troost and Berger 2014). Nolan et al. (2009) and Parker et al. (2012) review ACE applications, in which spatial complexity matters. Irwin (2010) provides a detailed analysis of the strengths and limitations of traditional economic modelling methods and of ABMs. The agent-based method has been intensively applied by other disciplines including geography with its explicit treatment of space (Brown et al. 2005; Robinson and Brown 2007; Crooks 2010), psychology with its rich representation of individual decision-making (Janssen and Jager 1999, 2001; Jager et al. 2000) and sociology with its explicit treatment of social networks (Carley 2009).

The ABM researchers have moved forward crossing the borders of single disciplines. Arthur (1993) opened the stage extending simple neoclassical models by advancing theoretical economic agents by means of computerized agents with learning algorithms, which were calibrated using human learning data from psychological experiments. Lux (2009) presents an empirical stock market ACE model where traders rely on the opinions of others when making investment decisions. Sun and Müller (2013) study payments for ecosystem services using an empirical spatial ABM where agents were influenced by opinions in their social network. Although significant progress was made, there still exist knowledge gaps. Firstly, the above-mentioned studies rarely combine economic choices, behavioral insights, influence of social networks and spatial aspects in one comprehensive model, which seems important to explore regional economics dynamics (Batten 2001). Secondly, while the use of empirical data in ABM is encouraged (Robinson et al. 2007), grounding behavioral rules (rather than agents' attributes) and interactions structure, e.g., social networks, of agents is still scarce. Thirdly, studies rarely perform a systematic test on how relaxing the neoclassical economic assumptions by including empirically observed behavior and social networks affects the development of a region and its economic activities.

This paper aims to make a step forward by addressing these three issues. We present an application of a spatial economic ABM to explore macrolevel changes at the regional level driven by a spectrum of microfoundations under various climate change scenarios. Microfoundations guiding agents' behavior in our case vary from a pure rational maximizer model to more behaviorally rich agents engaging in interactions within social network elicited from a survey. The model is applied to study economic decisions of farmers adapting to climate-induced drought risks in the Netherlands. Due to climate change, droughts are expected to occur more frequently and to become more severe in the future threatening crop production. Farmers need to adapt in order to secure their income and reduce losses of the agricultural sector in the region. However, there is a lot of uncertainty about the impacts of droughts and climate change. Studies have found that behavioral and social factors play the key role in farmers' adaptive decision-making.

This paper is particularly interested in investigating the effects of including empirical social networks and different behavioral rules guiding farmers' choices under drought risk on macroeconomic indicators (e.g., rate of adaptation, income of the agricultural sector) in the southwest Netherlands. Specifically, we seek answers on the following research questions: (1) What are the effects of microfoundations that allow social interactions and non-rational behavior on the regional drought vulnerability of the agricultural sector? (2) What is the impact of climate change on these macrometrics? In this study, we combine these aspects in an agent-based model of farmers' decision-making under drought risk. The goal of this paper is to investigate the effects of empirical social networks and different behavioral rules on farmers' choices under drought risk and its impacts on several macroeconomic indicators such as the rate of adaptation and income of the agricultural sector in the southwest of the Netherlands.

The paper is structured as follows. Section 2 discusses some theoretical considerations concerning farmers' adaptive decision-making under risk in more detail followed by the description of the case-study area. Details on the method including our specific ABM and the experimental design are presented in Sect. 3. Section 4 discusses the results. Conclusions, limitations and future work are listed in Sect. 5.

2 Droughts and the agricultural sector

2.1 Droughts and farmers' decision-making

Water is a vital production factor for the agricultural sector. Droughts are a worldwide problem and cause reduced crop quality, a loss of yield, increased production costs, a loss of farm income and anxiety about food security and increasing food prices. With climate change, the probability and severity of droughts are expected to increase in many parts of the world. Adaptation to climate change induced droughts is inevitable, and its success depends on the coordinated actions on governmental and individual levels. In order for public adaptation to be successful, adaptation decision-making at the farm level and its consequences for the performance of the agricultural sector at large need to be well understood.

Economic models, and specifically mathematical programming models, are frequently applied to investigate farmers' technology adoption in light of climate change (Janssen and Ittersum 2007; Gibbons and Ramsden 2008; Leclère et al. 2013). More specifically, many mathematical programming models exist that assess the interdependence between water availability, farm adaptation and regional agricultural income (Toft and O'Hanlon 1979; Benli and Kodal 2003; Maneta et al. 2009; Cortignani and Severini 2009; García-Vila and Fereres 2012; Connor et al. 2012; Graveline et al. 2014). In these models, a farmer's adaptive behavior depends on the flexibility to substitute between production factors and techniques formalized in the resource constraints and a farmer's decision rules stemming from expected utility theory. Mathematical programming studies mostly use some sort of aggregation employing the homogeneity assumption to avoid unmanageable model sizes and because of limited data availability. This causes aggregation bias, overspecialization and a weak goodness of fit of the model results on a regional level (Troost and Berger 2014). Even though many clever methods have been developed to address farmers' adaptive decision-making under uncertainty using mathematical programming models, it becomes more widely recognized that the representation of adaptive decision-making according to EU Theory is limited due to the underlying assumptions on rational actors and the absence of social interactions.

There is, for example, ample evidence that farmers' actual and planned decisions are guided by farmers' risk perceptions (Gbetibouo 2009; Deressa et al. 2011; Mandleni and Anim 2011; Wheeler et al. 2013; van Duinen et al. 2014b). Recent studies show that these risk perceptions deviate from the actual objective drought risk due to heterogeneity in their personal circumstances and personality traits. It shows, for example, that farmers are guided by the availability heuristic in their risk judgements; the more often farmers have experienced financial damage due to drought events the greater their risk perception (Tang et al. 2013; van Duinen et al. 2014a). Moreover, there is evidence that several subjective coping factors influence farmers' evaluation of adaptive strategies, such as perceived self-efficacy, perceived adaptation costs and perceived adaptation efficacy (Dang et al. 2014; van Duinen et al. 2014b; Gebrehiwot and van der Veen 2015).

Furthermore, there is empirical and experimental evidence showing that individuals do not take decisions under risk in isolation, but rather rely on social interactions within networks (Bougheas et al. 2013; Wossen et al. 2013). In the agricultural sector, informal peer networks are important channels for interactions. Empirical research shows that social peer influence is a significant variable in farmers' risk perceptions and adaptive behavior (Barnes et al. 2013; Tang et al. 2013; Dang et al. 2014). Barnes et al. (2013) show, for example, that the frequent use of social networks increases farmers' perceptions of climate change risks. Tang et al. (2013) found a positive relationship between connectedness to a social network with knowledge on water scarcity and a farmer's risk perception. Informal communications among peers provide references to validate one's risk perception and decision against the social norm.

The importance of social interactions in individual decision-making under risk and their contribution to the explanation of aggregate phenomena has been recognized in macroeconomics (Manski 2000; Brock and Durlauf 2005; Durlauf and Ioannides 2010). Based on new information from peers, agents learn about risks and adaptation options, changing their perceived adaptive capacity, and likely resulting in behavioral change (Kasperson et al. 1988). Interaction among heterogeneous agents regarding risks and adaptation options may result in some actions being simultaneously perceived as adaptive or maladaptive. Opinions and experiences of others impact individual decisions regarding adaptation giving rise to social reinforcement of certain trends in macrodynamics. Studies have shown that including social interactions may result in macrodynamics that differ significantly from macro-outcomes under the assumption of rational actors (Janssen et al. 2000).

From this we learn that psychological and social factors affect farmers' evaluation and ranking of adaptation alternatives and that they do not form perfect drought risk judgements based on probabilities and damages. Instead their expectations, preferences and decisions are likely to be biased and dynamic. Climate adaptation research calls for the need to explore the effects of social networks, perceptions and behavioral changes in order to understand the complex relationships and feedbacks between individual decision-making under risk at the microlevel, interactions through social networks at the mesolevel and aggregate- scale changes in vulnerability at the macrolevel. ABM is a useful method for examining the adaptive behavior of heterogeneous farmers whose past decisions impact future expectations. It allows the exploration of the interplay between individual decisions, social interactions and macroscale indicators.

Technology adoption of the agricultural sector has been studied using ABMs; see, for example, Schreinemachers et al. (2009, 2010) and Troost and Berger (2014). Several ABMs have been applied to study water availability and farm decision-making issues specifically (Berger 2001; Asseng et al. 2010; van Oel et al. 2010, 2012; Berger and Troost 2014). However, they mainly focused on the effects of heterogeneity and static behavioral preferences on model outcomes. Even though social networks are identified as important in studying agricultural technology adoption, few modelling studies include social network effects on individual decision-making and aggregate outcomes using empirical data. Manson et al. (2014) is to our knowledge the only available study including empirical social networks in the analysis of agricultural technology adoption. They show that social networks are important in the adoption of multifunctional agriculture and that their influence depends on their configuration.

Table 1 Damage to agriculture (Ministerie van Economische Zaken Landbouw en Innovatie 2011)

Degree of drought	Frequency	Damage (million euros)
Dry year	1/10	700
Extreme dry year	1/100	1800
Annual expected value		350

Current study contributes to this very scarce literature by examining the role of social networks on agricultural technology adoption in a risk context.

2.2 Case-study area

Even though the Netherlands is a ‘wet’ country with a maritime climate, it is likely that droughts will occur more frequently and will become more severe due to climate change. The initiation of the Deltaprogram, a national program with among other things the aim to secure the freshwater supply in the long run, shows that the Dutch government acknowledges the significance of future climate-induced drought problems (Ministerie van Verkeer en Waterstaat 2010). First estimates within the scope of this program indicate that the economic loss to the Dutch agricultural sector may reach 700 million € in a ‘dry year’ with a precipitation deficiency of more than 220 mm in summer (frequency of 1/10 years) (see Table 1). In an ‘extreme dry year’ with a precipitation deficiency of over 360 mm in summer (frequency of 1/100 years), the economic loss to the agricultural sector may reach 1800 million €. This is equal to 0.1 and 0.3 % of GDP, respectively. Due to climate change and socioeconomic developments, these damages might increase fivefold in 2050, meaning that the agricultural sector will face a loss of 700 million € once every 2 years (Ministerie van Economische Zaken Landbouw en Innovatie 2011).

The Netherlands’ southwest is a particularly vulnerable agricultural area. Historically, it is a transition area between fresh and salt water, causing groundwater and surface water resources to contain high chloride concentrations in many places. A distinction can be made between areas with and areas without access to an external water supply (see Fig. 1). Areas without an external water supply are dependent on natural systems, whereas areas with an external water supply have access to freshwater from lakes, rivers or pipelines (see Table 2).

Agriculture in Walcheren, Noord-Beveland and a large part of Zuid-Beveland exclusively depends on precipitation and fresh groundwater for its water supply. In these areas, excessive precipitation infiltrates the ground, forming a thin freshwater lens in the crops’ root zone. Under dry circumstances, the freshwater lenses disappear causing crop damage due to excessive dry and salty conditions. The proper functioning of the natural system is dependent on precipitation and evaporation. Farmers located in areas dependent on the natural system may adapt to drought circumstances by investing in freshwater basins in combination with irrigation equipment.

Goeree-Overflakkee and Tholen gained access to an external freshwater supply in 1970, when large compartment dams were constructed to protect the area from flooding, which created large freshwater lakes. Nowadays, water boards primarily

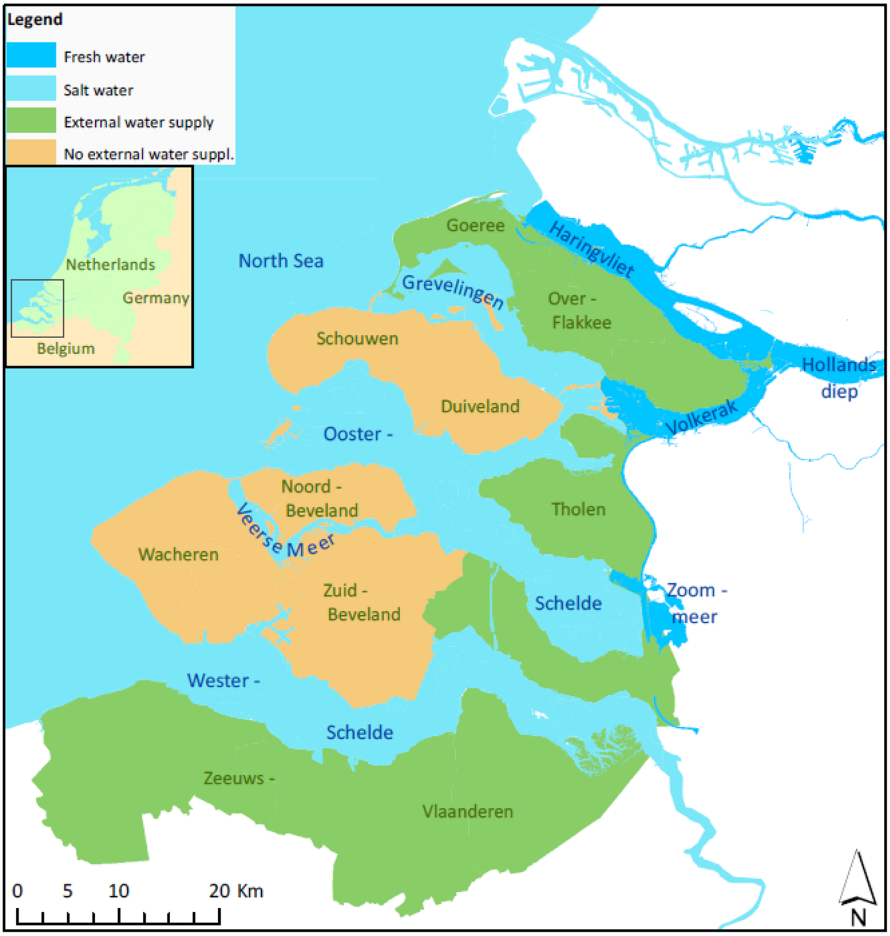


Fig. 1 Location of study area

Table 2 Freshwater supply in the Netherlands' southwest

System	Source of water supply	Geographical location
No external water supply	Natural system (i.e., only precipitation)	Walcheren, Noord-Beveland, part of Zuid-Beveland
External water supply	Natural system + water supply from lakes and rivers	Goeree-Overflakkee, Tholen, Zeeuws-Vlaanderen
	Natural system + water supply through pipeline	Part of Zuid-Beveland

use freshwater from these basins to flush the water system to contain salt concentrations in both the ground and surface water resources. The freshwater availability in these basins depends on river discharge. During droughts, river discharge declines

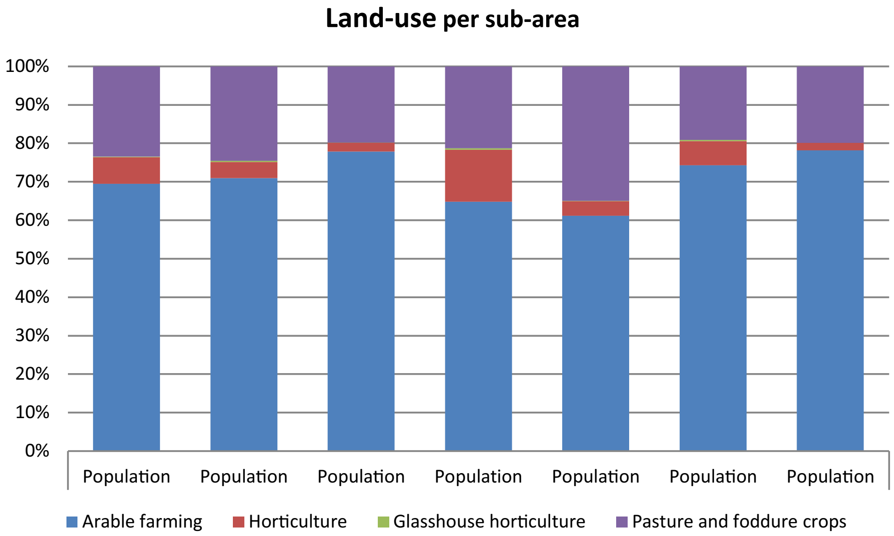


Fig. 2 Land use per subarea

reducing the availability of external water for flushing the system, irrigation and water supply to other sectors. In extreme dry situations, water boards may intervene by prohibiting irrigation. Zeeuws-Vlaanderen has historical access to freshwater from the regional water system in Belgium. On-farm water supply through pipelines is only available on Zuid-Beveland. In normal years with sufficient precipitation, this system provides an ample water supply. In dry years, however, the pipeline capacity is insufficient. Farmers located in areas dependent on the natural system in combination with an external water supply may adapt by investing in irrigation equipment only.

The total agricultural area in the southwest Netherlands is approximately 13,800 ha, cultivated by 3500 farmers. The land use across subareas is similar. Arable farming is the main land use in all areas, with potatoes, sugar beet and grain being the most cultivated crops (see Fig. 2). This is followed by pasture and fodder crops, mainly grass and corn. Horticulture is present in all areas. In Goeree-Overflakkee, the majority of the horticulture land is dedicated to flower bulbs. In Zuid-Beveland, 92 % of the horticulture land consists of fruit trees. In the other areas, it is a mix of flower bulbs, fruit trees and vegetables.

3 Methods

3.1 Agent-based model: basic structure

Building upon the experience of agricultural ABMs, we design an agent-based SAGA model (social networks in agricultural adaptation to climate change) to explore how farmers' choices under drought risk are affected by their social network and alternative

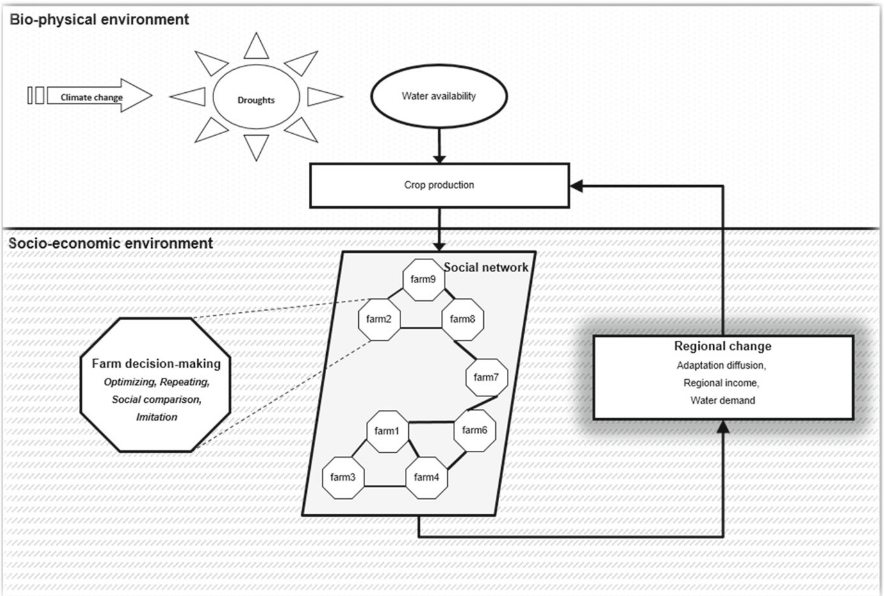


Fig. 3 Conceptual model

behavioral rules. SAGA advances the previous efforts by incorporating empirical data not only for the environment in which agents operate, but also for social networks through which agents interact. We are particularly interested in how farmers' adaptive behavior is amplified by social interactions and impacts the vulnerability of the agricultural sector. Therefore, we analyze the effect of climate scenarios on regional agricultural income, the adaptation rate of irrigation technologies and water demand as mediated by income generation through agricultural production and interactions in social networks. The conceptual model of SAGA is shown in Fig. 3. Following the ABM research tradition, an ODD+D model description is available in the electronic supplement of the paper (Grimm et al. 2006, 2010; Müller et al. 2013).

Farm agents operate in an environment consisting of the biophysical and socioeconomic sphere. Their decisions depend on and affect both of these environments. The biophysical environment consists of four components. Water availability is an exogenous model driver depending on drought conditions and the climate change scenario. We analyze two climate scenarios: 1. the current climate and 2. a climate change scenario. The climate change scenario affects the frequency and severity of drought events. Crop production is dependent on the water availability and, therefore, indirectly on the drought conditions and climate change scenario. Crops are produced on fields, and in the model, each field agent represents one cell of 1 hectare in a grid. Together, they define the geographical boundaries of the model. The four most important fields' state variables are the owner, the cultivated crop, the access to an external water supply and the applied irrigation technique. Depending on farmers' decisions, field agents may change from no irrigation to irrigation.

The socioeconomic environment consists of three components. Farm agents are at the core of the model; they own fields on which they cultivate crops and take decisions on the investment in irrigation equipment. Their income depends on the crop production in a specific year and, therefore, on the water availability and meteorological conditions. Farmers sell the crop yield on the crop market. In turn for their crops, they receive revenue, depending on the crop price. We consider the crop market as exogenous because input and output markets are beyond the scope of this regional study. Farmers take decisions depending on their drought risk experience and information from their social network. Farmers are connected to other farmers through social ties, and a farmers' social network is the collection of his social ties. Due to interactions within the network, information on the share of technology adopters in a social network is spread and is consequently affecting farmer's decisions. On the other hand, a farmer gives input to this network through its behavior, influencing the decision-making of others. Depending on farmers' decision-making strategy, they use drought risk experience and information from their social networks to decide whether to invest in irrigation equipment. This decision is crop dependent as some crops are more sensitive to droughts and therefore more profitable to irrigate. Farmers located in areas without an external water supply need to invest in additional equipment to store water, such as freshwater basins. Therefore, they are confronted with higher investment costs than farmers who are located in areas with an external water supply. Farmers' decisions collectively determine the performance of the regional agricultural sector at the macrolevel. In the model, the performance is measured through three indicators: the rate of adaptation diffusion, change in regional income and collective water demand.

Simulations are performed following a 10-day cycle to determine crop production; moreover, we use a yearly cycle for decisions on irrigation investments. Within each year, a sequence of three processes takes place: meteorological changes, crop production and farm decision-making. In the next section, the model implementation of each of these processes is discussed in more detail. The model is programmed in Netlogo 5.1.0 (Wilensky 1999).

3.2 Climate change scenarios

During the growing season (April–September), every 10-day crops are exposed to different climate conditions reflected in the ratio between actual evaporation (E_{act}) and potential evaporation (E_{pot}), and these are the model's input parameters. We analyze two scenarios: the current climate and a potential climate change scenario in 2100. The evaporation data are obtained from Mens et al. (under review). They estimated a 1000-year time series for the average potential and actual evaporation for the west Netherlands in the current climate scenario and a potential climate change scenario using a simple hydrological water balance model called RAM. The definition of the climate change scenario is based on the KNMI'06 climate change scenario,[1] W+2100, representing a change in average summer precipitation of −26 % (coastal

[1] KNMI is the Royal Dutch Meteorological Institute. It develops climate change scenario closely aligned with IPCC scenarios and specified for the Dutch situation.

areas) and an average change in temperature of +4 °C (Van den Hurk et al. 2006). The data on average actual and potential evaporation are uploaded to the SAGA model as a csv-file at initialization depending on the choice of a climate scenario. To account for uncertainty in climate variability each model run, the model chooses randomly a different starting date out of the 1000-year time series.

3.3 Crop production

To estimate agricultural yield loss, we use an agro-economic model called AGRICOM (Mulder and Veldhuizen 2014). Based on the ratio between actual and potential evaporation, AGRICOM calculates damage fractions for each type of crop. The damage fraction is the share of the potential crop yield that is lost due to drought, which is a standard approach to estimate agricultural damages. A crop's drought sensitivity depends on its growth stage; therefore, the damage functions change every 10 days, depending on the timing within the seasonal cycle. The damage fraction determines the survival fraction for the next time step, taking into account the part of the crop that is lost due to drought in previous periods. At the end of the year, the total damage fraction is calculated as the product of the remaining yield and the survival fraction summed over the year. This fraction is then multiplied by the potential crop yield to obtain the actual crop yield in kg/ha. The potential crop yield depends on the potential evaporation in a specific year. A detailed description of the crop damage model in the ODD+D description is available as online resource.

3.4 The farm agent

3.4.1 Economic decision model

At the end of the year, a farmer observes his potential and actual yield where the latter depends on whether there was loss from droughts or not in a particular year. Actual yield is estimated in SAGA for each location and each farmer based on the damage functions (coded in SAGA based on the calculations from the AGRICOM model) and farmers' adaptation choices. Based on this information, the agent calculates his actual gross margin (Y_t) and potential gross margin (Y_t^*). Following the standard economic approach, the actual gross margin is calculated as the sum over his actual yield Yld_t^n multiplied with the related crop price p^n minus the production costs c^n; see Eq. 1.

$$Y_t = \sum_{i=1}^{n} \left(Yld_t^n \cdot p^n \right) - c^n \tag{1}$$

The potential gross margin is calculated in the same way. Farmers observe their potential and actual crop production and consecutively estimate their income loss (L_t) based on potential income (Y_t^*) and actual income (Y_t) at the end of the growing season; see Eq. 2.

$$L_t = Y_t^* - Y_t \tag{2}$$

Agent-based literature offers various approaches to formalize bounded rationality. One of the methods is to assume myopic agents, agents who have imperfect information and only look backwards for information. Updating farmers' future expectations based on observed incomes from previous years is a common approach in the agricultural economics literature (Aurbacher et al. 2013). Thus, expectation formation in the current version of the SAGA model is implemented using a backward-looking algorithm assuming that farmers learn from past experiences.

For the income expectation formation, SAGA implements an exponential smoothening algorithm, in which negative experiences further away in the past count less than recent experiences as people tend to forget events further in the past; see Eq. 3. The weight a farmer attaches to more distant years depends on the discounting factor α. The discount factor is the weight a farmer attaches to previous years to account for the fact that farmers forget; events further away in the past get less weight than recent events. The discount factor alpha is constant over time. An exploration of other expectation formation algorithms including forward-looking expectations could be a valuable extension of the model.

$$\hat{Y}_{t_0+1} = (1 - \alpha)\, Y_t + \alpha \hat{Y}_t \tag{3}$$

Besides forming income predictions with the current farm plan and technology, farmers form expectations about their income if they would adopt irrigation technology. Farmers re-estimate Eqs. 1–3, assuming they apply irrigation. In this economic decision model, farm agents have perfect information about the costs and benefits of adopting the technology. On the one hand, agents take into account that adaptation through the investment in irrigation technology will increase the actual gross margin in dry situations as irrigation will increase the water availability and avoid drought-induced income loss; see Eq. 2. We assume an irrigation efficiency of 80 %, as part of the irrigation water does not reach the crop's root zone due to evaporation or runoff. On the other hand, agent calculates the extra production costs imposed by irrigation. The irrigation costs of a specific crop consist of variable costs including labor costs, energy costs, charges, and fixed costs. The variable costs are dependent on the predicted water use in mm and water price. The data on the cost parameters come from the AGRICOM model. These values are the average estimates of ground water and surface water irrigation technology, as we do not distinguish between these irrigation types. The fixed costs per ha depend on the capital recovery factor (CRF), the investment costs and maintenance and insurance costs. The CRF is the yearly annuity of an investment given a specific interest rate for capital and a time horizon. It takes a single payment and spreads it into a uniform series over N later periods. If the predicted crop income with irrigation is higher than the predicted income with no irrigation, a farmer decides to irrigate the crop. If the expected income with irrigation is higher than the income under the current farm plan, farmers will adopt the irrigation technology. See 'Appendix 1' for a decision tree of the economic decision model. When farmers decide to invest in irrigation of a particular crop, the field status in the ABM changes to 'irrigated.'

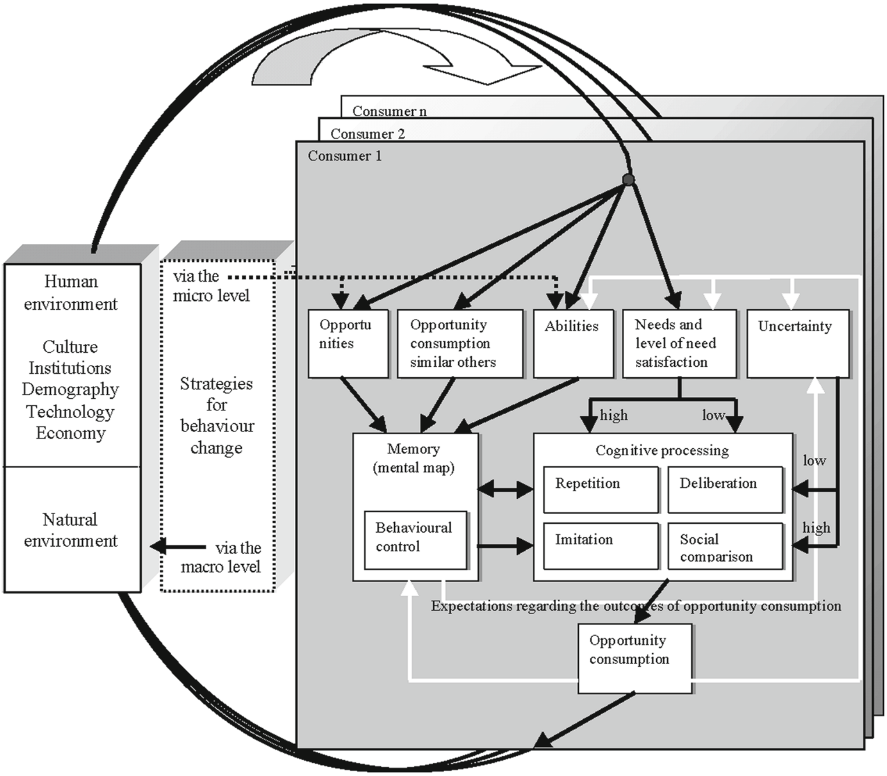


Fig. 4 The Consumat strategies

3.4.2 Individual decision-making and social interactions

While maximization under the assumption of perfect information might be an attractive way to conceptualize farmers' behavior, there is a lot of empirical evidence showing that economic choices under risk deviate from this model. Moreover, when faced with a decision under uncertainty people often rely on the opinion of their peers. We choose the 'Consumat' approach as a theoretical framework to conceptualize deviations from perfect maximization (Jager 2000). The Consumat approach has been developed as a framework that allows for the modelling of different decisional strategies as a function of satisfaction and uncertainty. It thus allows for agents to switch between decision strategies that differ concerning social orientation and cognitive effort. The key decisional strategies are repetition, imitation, deliberation and social comparison, as shown in Fig. 4 (Jager 2000; Janssen and Jager 2001; Jager and Janssen 2012).

When an agent is satisfied and certain, it will repeat its previous behavior. This cognitive simple strategy reflects habitual behavior. Imitation is performed when the agent is satisfied but uncertain. In this simple social strategy, the agent will copy the behavior of another (similar and connected) other agent. Social comparison is performed when an agent is uncertain and not satisfied. This more cognitively demanding strategy involves the scanning of other agents' behaviors and estimating the outcomes for copying that behavior. Deliberation finally is a cognitive demanding strategy performed when an agent is not satisfied and certain. Deliberation involves the evaluation of all possible behavioral options and thus resembles optimizing behavior.

The Consumat approach allows for integrating different theoretical concepts from social sciences, such as needs, decision strategies, cognition and social interaction into a framework for agent-based modelling. The four decisional strategies are basic orientations of the decision-making process, and depending on the modelling demands, it is possible to develop different implementations of these strategies, e.g., time horizon, time-discounting functions, opinion-change functions, effects of expertise and the like, thus addressing a much wider spectrum of decisional strategies.

In comparison with many approaches that use, e.g., optimization with imperfect information, or bounded rationality, the Consumat approach is capable of addressing the switching between different decision strategies in a more realistic manner. For example, the Consumat approach allows for modelling agents performing habitual behavior, and when the outcomes of this habit are not satisfactory anymore, or the agent gets uncertain, it may search for alternative behavior using the other decision strategies. When this new behavior is satisfactory, and the agent is certain, a new habit may emerge. These processes are critical in understanding the dynamics of innovation diffusion.

There are several ABMs that employ the Consumat approach. In some studies, the allocation of the four Consumat decision-making strategies is forced upon the model and remains static over model runs (Sopha et al. 2013). Alternatively, the choice of decision-making strategy is endogenous and dynamic depending on the evolution of an agent's satisfaction and uncertainty over time (Speelman 2014; Natalini and Bravo 2014; Miahle et al. 2012). In the SAGA model, the assignment of a decision-making strategy of an economic agent evolves over time, depending on his level of income satisfaction and uncertainty. Uncertainty and level of income satisfaction change depending on the weather, crop production and income. Therefore, agents may switch between decision-making strategies at a later point in time. To make agents' cognitive strategy dependent on their experience in SAGA, we define income satisfaction and uncertainty within the model as well as the income aspiration level and uncertainty tolerance thresholds. Both are heterogeneous across agents.

Income satisfaction (*S*) is defined as the ratio between a farmer's current income Y_t and his potential income Yt^*; see Eq. 4. The income aspiration level, the level of income that agents aspire in order to be satisfied, is heterogeneous across agents. We assume that the income aspiration level is normally distributed across the agents, with $N(0.5, 0.17)$.[2] The level of income satisfaction determines a farmers' cognitive effort to make decisions. Satisfied farmers rely on decision-making strategies that do not require a lot of cognitive effort, for example repetition or imitation. Unsatisfied

[2] In a sensitivity analyses, we explored the sensitivity of the model results to an alternative distribution. Implementing a uniform distribution $U(0, 1)$ did not have any significant effects on the model results.

farmers, however, will make a lot of cognitive effort to make a decision that will make him better-off in the future, for example through deliberation or social comparison.

$$S_t = \frac{Y_t}{Y_t^*} \tag{4}$$

Decision-making under risk is operationalized in the Consumat model as a farmers' level of uncertainty concerning his income given the probabilistic nature of drought events and the adoption of irrigation technology. A farmer's uncertainty level, or risk awareness, is defined as the ratio between a farmer's current income Y_t and his predicted income $\hat{Y}_t$; see Eq. 5.

$$\mathrm{UT}_t = 1 - \frac{Y_t}{\hat{Y}_t}, \quad \text{for } \mathrm{UT}_t > 0 \tag{5}$$

We assume that the uncertainty threshold is normally distributed across the agents, with $N(0.5, 0.17)$ (see footnote 2). A farmer's uncertainty determines whether a farmer engages in social interactions to make an informed decision. Agents who are uncertain are more likely to engage in strategies involving social interactions. Farmers, who are certain, are unlikely to engage in social interactions to inform their decision-making and instead rely on their own experience.

Based on a farmer's uncertainty, income satisfaction, income aspiration level and uncertainty threshold he will engage in one of the four Consumat decision strategies: repetition, imitation, deliberation or social comparison. When agents are satisfied and certain, they will simply repeat their behavior next year (*repetition*). This implies that when the climate is stable, farmers are not likely to change their behavior. However, when droughts occur farmers are likely to face crop damage and income changing their level of income satisfactions and uncertainty. Depending on a farmer's income aspiration level and uncertainty threshold, he will rely on another decision-making strategy in the next year. Unsatisfied but certain agents rely on *deliberation*. This decision strategy is an equivalent of the 'economic' strategy described in Sect. 3.4.1 in which agents have perfect information, systematically compare decision alternatives and make optimal choices and is implemented in exactly the same way. This model setup allows us to systematically compare an individual optimization strategy with individual choices based on heuristics (repetition) as well as with economic choices influenced through the social network.

Two decision strategies consider interactions within social networks. Uncertain agents will base their decisions on the behavior of others, for example through *social comparison* or *imitation*. In the case of *imitation*, an agent evaluates the behavior performed by its strong links. A strong link joins peers who have similar farm characteristics and are located nearby. The behavior of a particular share of strong links is imitated.

Finally, an agent who relies on social comparison considers the behavior performed by both its weak and strong links and its whole social network. Weak links join less similar and more distant farmers than strong links. The behavior of a particular share of farmers within his network is adopted. This decision strategy requires more cognitive effort than imitation. See 'Appendix 1 and Appendix 2' for the decision trees per Consumat strategy.

3.4.3 The data on microfoundations of agents' behavior

Agent parameterization To create an empirically based agent population, the farm agent attributes are calibrated based on survey data. During January and February 2013, a survey based on a potential sample of 1474 members of a Dutch agricultural organization (the LTO) was conducted to elicit farmers' drought risk awareness, adaptive behavior and socioeconomic characteristics. TNS-NIPO, a Dutch organization specializing in data collection on the basis of questionnaires, supported the survey design, web application, communication with respondents and database management. The survey was pretested in 12 interviews with farmers, in consultation with Scheldestromen (the local water board) and LTO. To stimulate responses, at least one reminder was sent out and people were offered a chance to win a lottery prize. In total, 142 responses (9.3 %) were received. In the survey, respondents were asked to indicate their farm size and cropping pattern. To randomly generate an agent population based on this sample in SAGA, we followed Berger and Schreinemachers (2012), who use Monte Carlo techniques. In line with their approach, we determined empirical cumulative frequency distributions for the cultivated area of 10 crops. These functions are then used to randomly allocate an area of a specific crop to an agent.

Adaptation choices To elicit farmers' adaptive behavior in the survey, we have considered adaptation measures fitting the geographical, economic and institutional context of the southwest of the Netherlands. The drought adaptation strategies to be included in the survey were selected in three stages: (1) selection based on the biophysical conditions and secondary literature review; (2) external validation through interviews with experts; and (3) fine-tuning based on the feedback from farmers. Firstly, we left out farm adaptation strategies not directly related to drought risk, such as diversification of farm activities, the selling/buying of land and the relocation of farms. Tolk (2012) overviewed all relevant adaptation measures to drought and salinity in the southwest of the Netherlands.

From this overview, we shortlisted several measures on the basis of a single criterion: the ability of farmers to implement the adaptation measure independently from institutions such as agricultural cooperatives and regional/local governments. Adaptation measures concerning spatial planning, water pricing and large-scale infrastructure have therefore not been included in the analysis. Secondly, the set of adaptation strategies was very carefully set up and externally validated. We reviewed the set of measures and consulted experts with local knowledge. The experts included water management specialists from the local water board and agricultural specialists from organizations in the Netherlands. Thirdly, we tested the survey and the set of adaptation strategies in several in-depth interviews with farmers, resulting in 12 adaptation measures for the final survey; see 'Appendix 3.'

However, at this stage we have implemented only two adaptation options in the model: irrigation and freshwater storage in basins. For farmers in areas with an external water supply it suffices to invest in irrigation, whereas farmers located in areas

Table 3 Model experiments

No.	Behavioral rules	Climate scenario	Social influence
Exp1	Optimization	Current climate	None
Exp2	Optimization	WP2100	None
Exp3	Consumat	Current climate	Yes
Exp4	Consumat	WP2100	Yes

without an external water supply have to invest in an additional freshwater basin for their water supply increasing their investment costs. Note, the survey data allows us to test 12 options. Understanding the diffusion of various adaptation options under various behavioral assumptions (perfect maximizers vs. Consumat farmers with social interactions) for different climate change scenarios is a subject to future work.

Social network To identify farmers' social networks, we relied on the homophily principle in which the degree of similarity structures one's social network (McPherson et al. 2001). The survey contained a question to identify a farmer's number of connections: A respondent had to mention the 5 most important peers with whom he interacts on drought issues followed by two questions to elicit an agent's similarity to the most important peers within his social network based on distance and farm type. To calibrate the social network in the SAGA model, we followed a similar approach as the Monte Carlo techniques to calibrate farm size and cropping pattern. In the model, farmers who are nearby and who have similar farm types have a higher chance to form a social tie. Social ties that are very similar are defined as strong links, and connections that are less similar are labelled weak links.

4 Results

4.1 Experiment setup

We modelled farmers' adaptive decision-making under different climate and behavior scenarios (Table 3) to answer our research questions. A comparison of Exp1 and Exp2 to Exp3 and Exp4 sheds light on the differences in regional dynamics depending on the assumptions about economic agents' microfoundations. By contrasting Exp1 and Exp3 with Exp2 and Exp4, one can infer the differences economic systems may experience when adapting to natural hazard risks under various climate change scenarios and behavioral microfoundations. Zooming into the temporal patterns of the distribution of behavioral strategies in Exp3 and Exp4 allows us to judge the potential factors explaining the dynamics behind macrometrics. Each scenario is run for 30 years 30 times to account for a random seed effect.

4.2 Macrometrics of interest

To explore the effects of various microfoundations on the regional dynamics in our case-study application, the SAGA model traces several macrometrics. The results

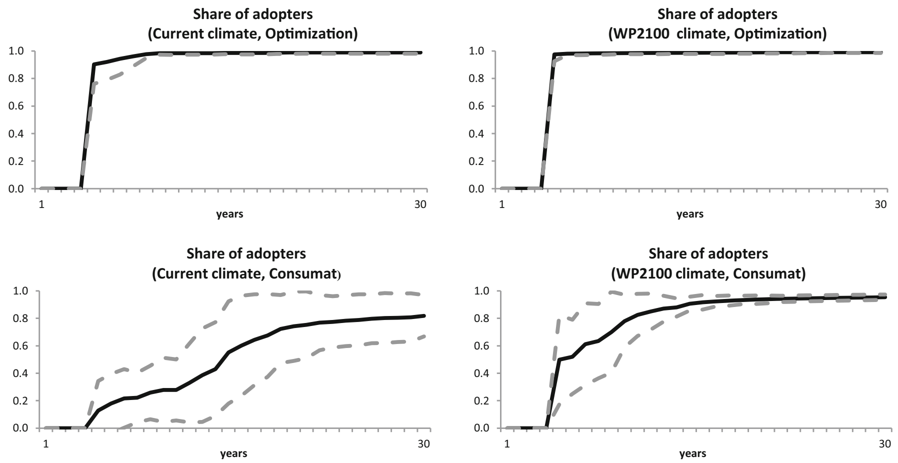


Fig. 5 Share of adopters (Exp1, Exp2, Exp3, Exp4)

of the 4 SAGA experiments for economic, environmental and social measures on the regional level are presented below. Each macrometric for each experiment is presented as an average over 30 runs to control for the random seed effect. Finally, our ACE model allows recording all agents' decisions and considerations on individual level in csv-files. This allows one to look at the disaggregated dynamics and interactions driving averaged cumulative numbers and macrophenomena. Section 5 will discuss the outcomes.

Rate of adopters The *rate of adopters* gives insight in the dynamics of the adaptation process (see Fig. 5). The rate of adopters is measured as the share of farm agents who adopts irrigation on at least one of his fields.

Change in regional agricultural income To get insight in the aggregate-scale change in the drought vulnerability of the agricultural sector, we measure the *change in regional income* (see Figs. 6 and 7). Regional agricultural income is measured as the sum of individual income over the whole population.

Cumulative water demand Finally, we monitor the *cumulative water demand* of farmers who are located in areas with an external water supply (see Figs. 8, 9). The cumulative water demand is determined by two factors: the meteorological conditions and the irrigated area; the extent of the application of irrigation.

Behavioral strategies We also measure the share of farmers' population employing the maximization strategy or one of the other three Consumat strategies in Experiments 3 and 4 (see Fig. 10). This allows to clarify the role of social networks in order to explain the adoption patterns observed in Fig. 5. Note that all farmers are maximizers in Experiments 1 and 2.

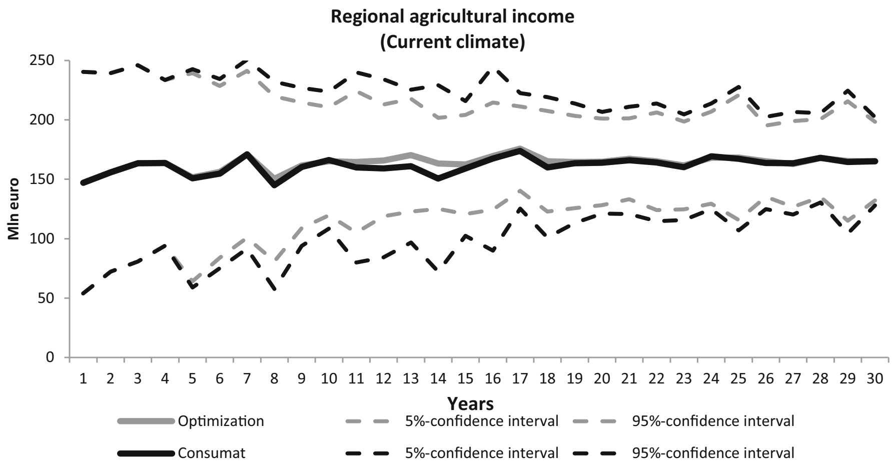


Fig. 6 Regional agricultural income in the current climate (Exp1 and Exp3)

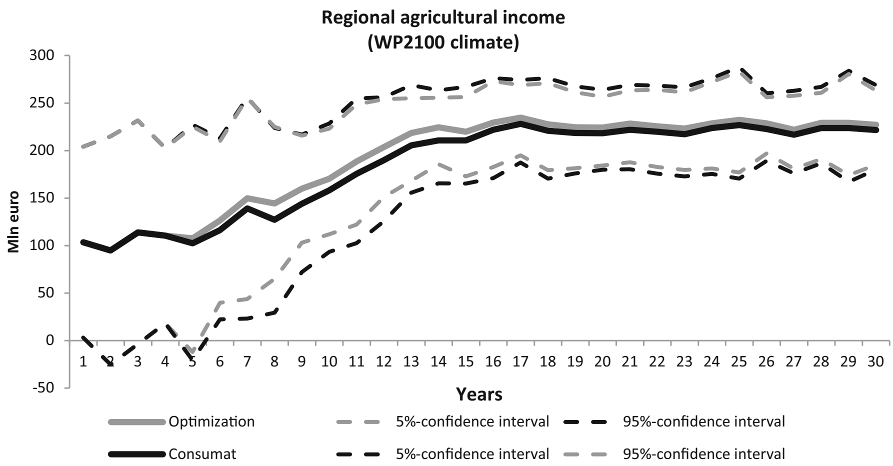


Fig. 7 Regional agricultural income under climate change (Exp2 and Exp4)

5 Discussion

5.1 Economic optimizers, heuristics-based farmers and impacts of social network

One of the primary questions we want to explore here is to understand how aggregated economic, social and environmental measures vary with different microfoundations at the individual agent level. For this purpose, we compare the macrodynamics in the region assuming that farmers agents behave as economic maximizing (Exp1 and Exp2, Table 3) versus heuristic-based agents potentially affected by their social network

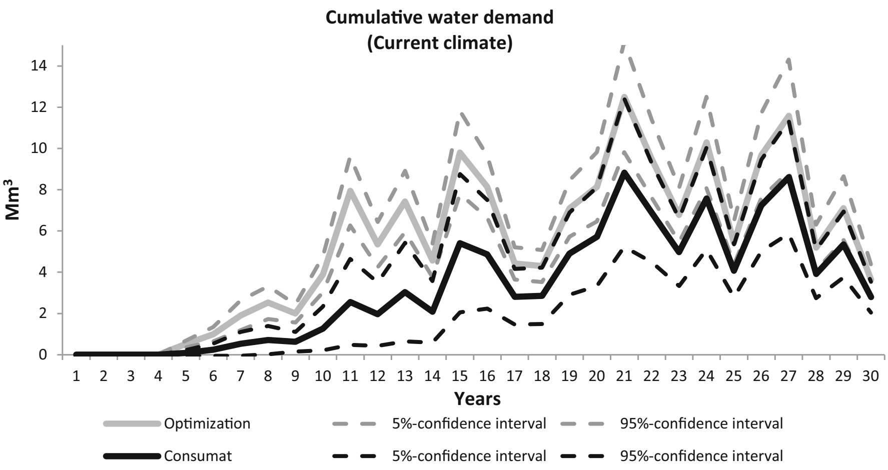


Fig. 8 Cumulative water demand in the current climate (Exp1 and Exp3)

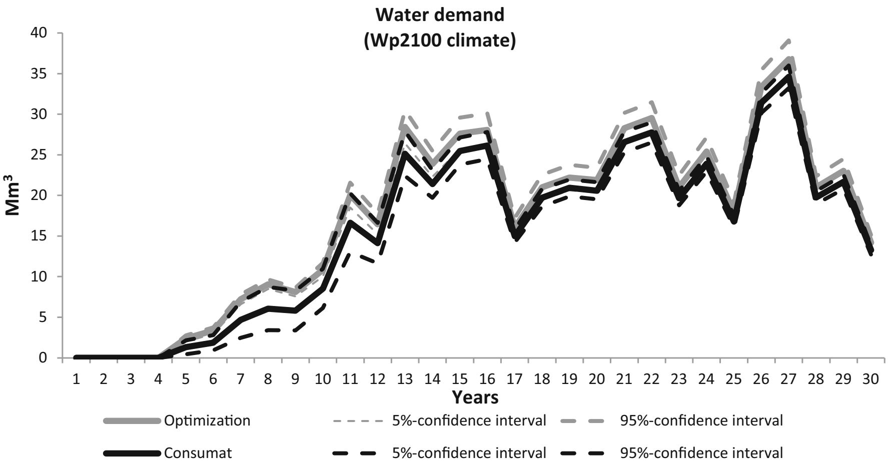


Fig. 9 Cumulative water demand under climate change (Exp2 and Exp4)

(Exp3 and Exp4, Table 3). In both cases, the agents' population is parameterized using survey data, including data on social networks.

5.1.1 Share of adopters

Figure 5 shows the dynamics of the share of adopters for the two climate scenarios assuming that farmers rely on rational economic decision-making (Exp1 and Exp2). Both in the current climate and under climate change nearly all farmers (98 %) adopt irrigation on at least one of their fields as an adaptation option to tackle the adverse effects of droughts. We observe this dynamics because rational farmers' expected benefits of irrigation do not compensate the expected adaptation costs in the early

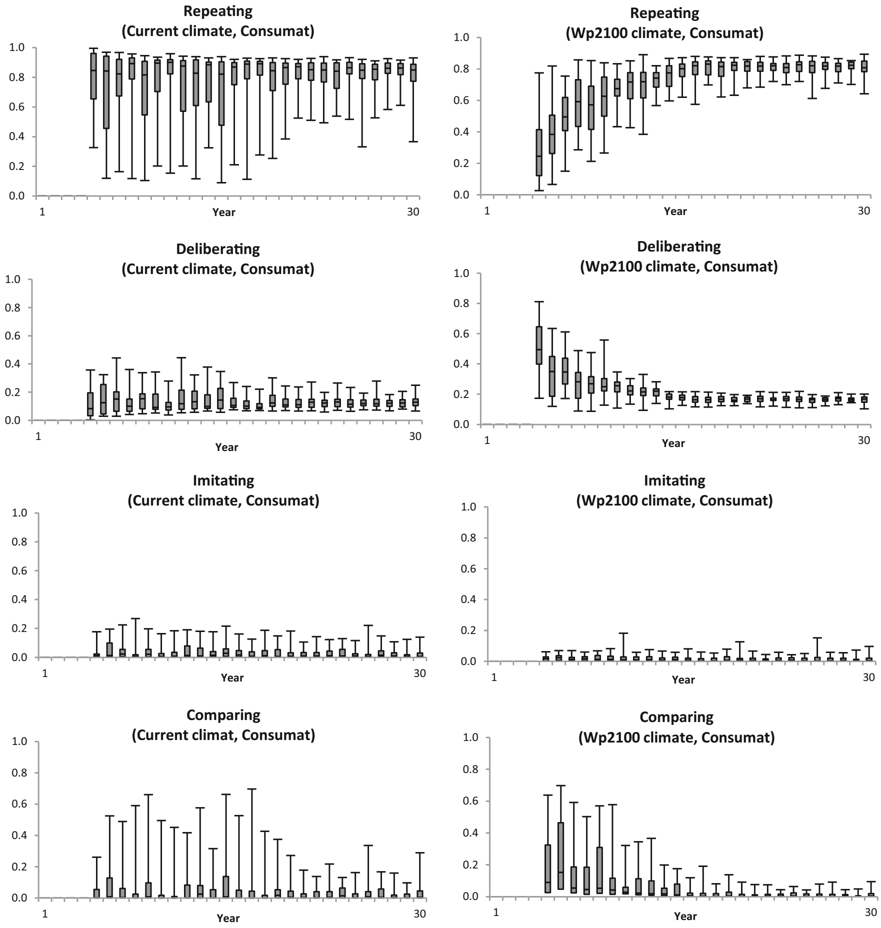


Fig. 10 Dynamics of Consumat strategies in two climate scenarios (Exp3 and Exp4)

periods due to relatively mild droughts, and consequently losses. At the same time, as soon as expected losses due to droughts grow and exceed benefits of adaptation, the transition to an almost complete adoption of the drought adaptation technologies happens quite abruptly. Note that this 'nearly one shot' transition happens in the population of farmers that are heterogeneous in the size of their land, cropping patterns and income. Yet, this is rarely a pattern one observes in the real world (Rogers 2003).

Thus, we explore the dynamics of the share of adopters when farmers behave according to the Consumat decision-making strategies, also for two climate scenarios (Exp3 and Exp4, Fig. 5). So, the adoption rate in the Consumat scenarios with the optimization scenarios shows that the average share of adopters follows a very different path over time for both climate scenarios. Specifically, it shows that the adoption process takes several years and is not an abrupt transition. The functioning of social networks is the key to explain this gradual process. In the Consumat scenarios (Exp3 and Exp4), a share of the farmers relies on decision-making strategies (imitation and social comparison) that involve social interactions through their social networks. Once these farmers observe that the majority of their weak or strong links have adopted, they will also decide to adopt. This process takes time, as the adoption process should be start up by farm agents who rely on deliberation (economic optimization). In order to explain the differences in the adoption patterns of the Consumat scenarios across climate scenarios, Sect. 5.3 explains more about the dynamics of switching between the behavioral strategies and the consequences for the evolvement of the adoption rate.

5.1.2 Dynamics of the regional agricultural income

We monitor the aggregate-scale effects of the different adaptation pathways presented in Fig. 5 on regional income and cumulative water demand. Figure 6 presents the regional income for both the optimization and Consumat scenario in the current climate (Exp1 and Exp3). In the current climate scenario, the average regional income stays more or less constant over time. However, the confidence intervals show that the variation in income is decreasing over time, due to the adoption of irrigation technology. These results have two implications. Firstly, due to irrigation farmers observe less income loss in the case of dry conditions. Secondly, in good years in which dry conditions are absent the additional income generated with irrigation do not compensate the involved irrigation cost resulting in lower income peaks.

Comparing the optimization scenario with the Consumat scenario shows that the difference in average regional income between these two scenarios is small. The Consumat scenario, in which agent relies partly on their social networks, shows a slightly lower income between 7 and 20 year. The average regional income in this period is 2.3 % lower, and the 95 % confidence interval is larger with the lower endpoint being 18.5 % lower and the upper endpoint being 6.7 % higher on average. The lower endpoint is the result of the slow adoption process in this phase of the scenario. Due to the slow adoption, a large share of the farmers is still exposed to drought conditions and face more income loss. However, after 30 years the differences in income mostly vanish.

Under the current model assumptions, the income trends in Fig. 6 reveal that even if there is only a small share of economic agents who behave as rational optimizers, a population as a whole still may produce results that are close to model with only maximizing agents. In other words, it is enough to have just a small proportion of perfect maximizers within a population of heuristics-based agents who have an ability to imitate the best practice in their social network to achieve a near-optimum state of the regional economy in the long run.

The advantage of this result is twofold. Firstly, this may actually appear quite in harmony with the reality: when there are few leaders who perform careful and costly analysis and others follow their choice if they observe a successful performance. At the same time, it implies that in some circumstances the economic model with its assumptions of rational perfectly informed agents would predict an economic trend that a real economy follows despite its misrepresentation of the actual heuristics-based behavior. Yet, this is valid when social interactions are present. Secondly and reversely, there is no need to have an assumption of perfect information as in some circumstances

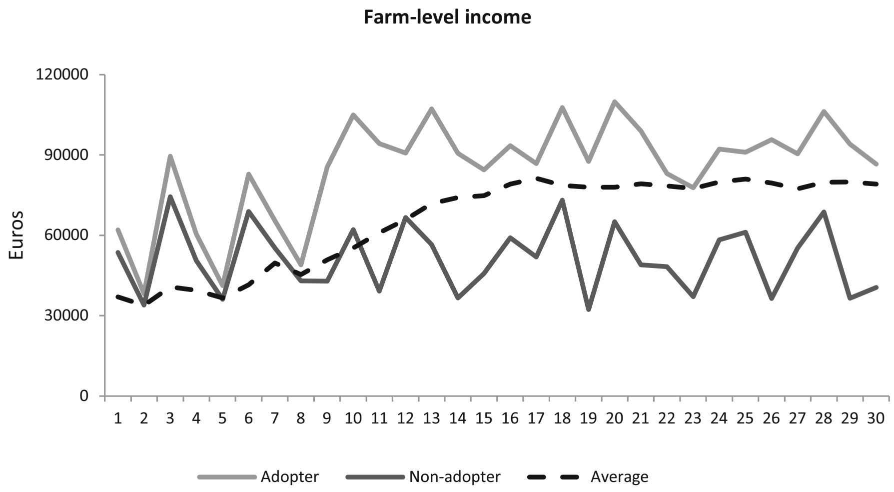


Fig. 11 Farm-level income of three Consumat farmers under climate change (Exp4)

less computationally heavy agents deliver aggregated results that are close to the optimum on the macrolevel by just copying a few 'intelligent' agents. Figure 11 shows income trend of a farmer who successfully adapts to drought, a farmer who does not adapt and an 'average farmer' in the Consumat with climate change scenario (Exp4). The 'average farmer' is the representative for the whole population and is simply the average income trend of all farmers. The other two represented farmers have been selected based on their similarity, so they are located in the same area, have a similar cropping pattern and have a similar farm size. However, due to heterogeneity of behavioral properties they make different choices. One of them adopts, resulting in a considerable income increase, and the other one is a laggard and does not adopt. Farmers' uncertainty thresholds, aspiration levels, social network characteristics and expectations are important behavioral characteristics that determine their adaptive behavior. Farmers who rely on deliberation or farmers who have strong social networks that they use for their decisions have the highest chance to be successful.

This figure also shows that interpreting model results based on an average or representative agent may be misleading, especially if farmers are not behaving in a rational way. The aggregate results show that with climate change the regional income is increasing under the current model assumptions; however, if all farmers would be able to adapt, income might be even higher. This makes it an important task to identify the farmers who are not able to adapt under climate change and to think about policy instruments on how to influence these farmers.

5.1.3 Water demand

The cumulative water demand shows how much water farmers demand from the water system, and this includes only farmers who are located in areas with access to an external water supply as farmers who are located in areas without an access to an external water supply do not have access to these resources. Figure 8 shows the cumulative water demand in the current climate; Fig. 9 shows the cumulative water demand under climate change. Due to the adoption of irrigation, the water demand increases over time and is dependent on the irrigated area. The variability depends on the meteorological conditions in a specific year. In a dry year, the cumulative water demand peaks.

In the optimization scenarios, the cumulative water demand is higher than in the Consumat scenarios. In the current climate with optimizing behavior (Exp1), the average water demand is 46 % higher than in the current climate with Consumat behavior (Exp3). Under climate change, the average difference in cumulative water demand between Consumat behavior and optimizing behavior is 13 % (Exp2 and Exp4). The increase in cumulative water demand in the case of optimizing behavior can be explained by the fact that in the Consumat scenarios the share of adopters is lower than in the optimization scenarios and fewer farmers adopt irrigation resulting in a smaller irrigated area and consequently in a lower water demand. Thus, there is a significant qualitative difference in the trend of cumulative water demand. From a water demand point of view, Consumat farmers deliver more resilient outcomes in the face of deceasing water availability.

5.2 Adaptation to climate change under various behavioral assumptions

Due to effects of climate change on droughts, the average regional income is 50 million euro lower in the first years of the simulation compared to the current climate and even becomes negative in some of the experiments (Figs. 6, 7). Therefore, the majority of farmers adopt irrigation techniques quickly in this climate scenario. In the current climate, it is unprofitable to irrigate crops that are not very sensitive to drought conditions. However, as droughts become more severe and frequent with climate change it becomes profitable to irrigate these crops as well, resulting in an increased irrigated area.

Consequently, the average regional income nearly doubles within 10 years and the income variation decreases. Remarkable is that the average regional income becomes higher than that in the current climate scenario, and it increased by approximately 33 %. This can be explained by the fact that under climate change the potential crop production increases; due to increased temperatures and more sunshine the potential evaporation of the crop increases. The potential crop production is here defined as the maximum crop production under the assumption that enough water would be available to fulfill the crop's water requirement.

These results should be interpreted carefully as it may convey the impression that climate change is good as it eventually results in income growth. However, the increase in regional income is accompanied by a large increase in the collective water demand. In the case of climate change, the cumulative water demand increases approximately with a factor 2 and 5 (Figs. 8, 9). A main question remains to what extend the water system will be able to facilitate the demand.

In this analysis, we assumed that the irrigation water demand from the external water system can be met both in the current climate and in the case of climate change. Indirectly, we assume that publically financed infrastructure or policy instruments are in place to facilitate agricultural water demand. However, recent evidence shows that currently in extreme dry years, the water demand cannot be met and that large public and private infrastructural investments are required to facilitate irrigation water demand in the future. Furthermore, usually these are long-term investment and there could be a significant time lag between the moment of decision to go for irrigation and the actual ability to use it effectively. Through these model assumptions, many other economic costs are not accounted for, for example the effect of large public adaptation investments or the effects of policy instruments on the agricultural sector and the rest of the economy. An important question to address in future research is whether it is cost-effective to facilitate this water demand.

5.3 Switching between behavioral strategies

Figure 5 shows that the adoption process in the Consumat scenarios is delayed compared to optimization scenarios due to the reliance on social network for adoption diffusion. Specifically, this figure shows that the path of the share of adopters follows an S-shaped curve, which is a standard empirical stylized fact in the field of technology diffusion (Rogers 2003) and that, compared to the climate change scenario, it takes more time for the adoption process to set off. In the first stage, farmers are reluctant to adopt up to a certain point where the adoption rate increases and finally stabilizes.

To clarify this pattern, the left side of Fig. 10 shows the dynamics of the share of farmers switching between the four Consumat decision strategies in the current climate scenario. In the beginning of the experiment, the majority of farmers is relying on repetition, indicating that this group is satisfied and certain. And, consequently, they have no incentive to change their behavior. However, the figures of the other strategies and the spread of the results show that this is very much dependent on climate variability. Depending on the climate variability in the beginning of the experiment, farmers may become unsatisfied with their income and rely on deliberation or become uncertain and rely on imitation or social comparison.

However, even though some farmers are uncertain and/or unsatisfied in the current climate, Fig. 5 shows that they are reluctant to adopt in the current climate; farmers who rely on any other decision strategy than repetition do not adopt because the information they acquire is not convincing enough to change their behavior. In the case of farmers who rely on deliberation (i.e., equal to economic optimization), this information is a calculation of the expected costs and benefits of adoption. For many farmers, the adoption benefits do not compensate the adoption costs in the current climate, and therefore, only few of them adopt irrigation. For farmers who rely on the strategies imitation and social comparison, the information is coming from their social network. Once they observe that the majority of their weak or strong links have adopted, they will also adopt.

In fact, the adoption process should be initiated by farm agents who rely on deliberation, as agents who rely on strategies involving social interactions only adopt when the majority of their connections have adopted irrigation. This process is slow in the current climate, only few farmers that rely on deliberation actually adopt, and therefore, it takes a long time before the farmers who rely on their social network observe a majority of adopters of their weak or strong links. However, once a certain number of deliberators have adopted, this is observed by agents relying on the Consumat strategies involving social interactions, causing a nonlinear increase in the rate of adoption (see Fig. 5). These results can also be traced back in Fig. 10. After more than 15 years, an increasing part of the farm population switches from social comparison, imitation or deliberation to repetition, indicating that they are satisfied and certain after they adopted irrigation.

The same underlying mechanisms play a role in the adaptation process in the climate change scenario (see right side of Fig. 10). In first simulation years of this scenario, fewer farmers rely on repetition and more farmers rely on deliberation than in the current climate, indicating that they are more unsatisfied. This makes sense as droughts become more frequent and severe in the climate change scenario, affecting farmers' income and consequently their level of satisfaction. Combining the results of Fig. 5 and the right side of Fig. 10 shows that the farm agents who rely on deliberation judge the adaptation options profitable under the climate change conditions. This causes many early adopters compared to the current climate scenario. Consequently, other farmers who rely on imitation or social comparison observe the adoption in their social environment and also decide to invest in irrigation equipment. Many of the farmers who have adopted irrigation become certain and satisfied; this is shown by the large number of agents that change to repetition.

6 Conclusions

This study has examined the effect of non-optimizing decision strategies and social networks on the adoption of irrigation technologies across farmers in the southwest Netherlands under several climate change scenarios. An ABM was developed which is able to simulate the effect of droughts on crop production, farm income and farm decision-making. Several aspects of the model are calibrated based on empirical survey data, and most importantly, this paper is one of the first attempts to include empirically calibrated social networks in the analysis. Four experiments were conducted combining two climate scenarios with two behavioral scenarios. The results provide several insights in the role of heuristics, social networks and climate change on farmers' adaptation pathways.

When farm agents rely on heuristics and social networks, the adoption process follows a different path than under optimization. The adoption process takes more time as farmers rely on information flows within their social network to inform their decisions. When agents do not observe a satisfactory number of adopters in their social network, they remain uncertain and are reluctant to adopt. Once a particular threshold of number of farmers has adopted the technology (critical mass), the adoption process through social interactions takes off.

Uncertainty about the effects of climate change slows down the adoption process. In the current climate, the adoption process through social interactions is slower than under climate change. A large variability in climatic conditions and relatively mild droughts affect farmers' feelings of uncertainty, satisfaction and expectations on the profitability of adaptation options. This causes a slower adoption of irrigation technologies across the deliberators than with climate change. With climate change the adoption process through social interactions takes off more quickly. Drought events become more extreme, and farmers are less uncertain about their decisions. Consequently, a large share of the farmers rely on deliberation and adopt quickly, followed by other agents in their social network.

The delay in adaptation causes a loss of income in the short run compared to a situation with perfectly rational behavior. However, in the long run the difference in income vanishes. In the current climate, there is a very small effect of adaptation on average regional income. However, the variability in regional income is reduced due to adaptation. The regional income under climate change increases due to large-scale adaptation and higher potential crop production. Investigating regional economic dynamics based on behaviorally realistic agents shows that it suffices to have a few rational agents and a well-functioning social network in order for the system to adapt and show economic optimal behavior in the long run.

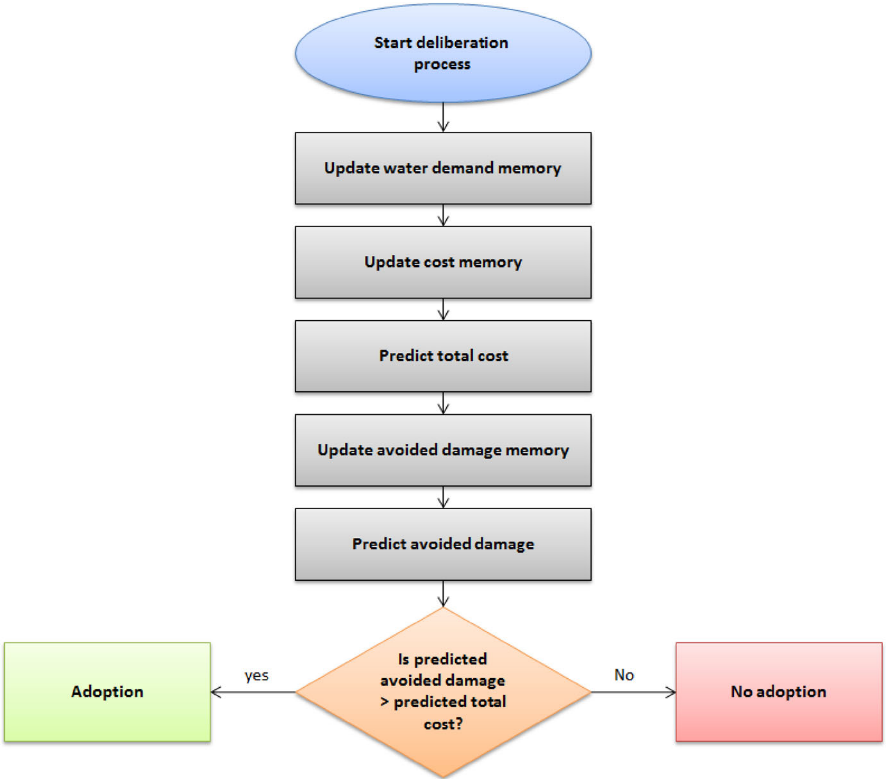
Heterogeneity of farmers' behavioral properties allows us to identify successful and unsuccessful farmers and to develop tailor-made solutions. Future in-depth studies to the causality between farmers' behavioral properties and successful behavior are in demand. In this situation, a farmer's feeling of uncertainty and the functioning of social networks may be the key to stimulate adaptive behavior in the short run and to consequently to avoid income loss in the short run.

However, these results should not be interpreted too positively. We cannot sit back and wait. The higher income under climate change goes accompanied with a huge increase in water demand. The question remains whether the water system is able to facilitate this demand. The answer to this question points in a negative direction, as river discharges are expected to decline in the future due to climate change induced droughts in the Netherlands and developments in upstream countries. Farmers have been served with sufficient water and good quality for several years; therefore, they may rely on the government to act against the negative effects of climate change. Reliance on public adaptation has been identified as one of the major barriers toward adaptation to climate change. A future challenge will be to align public and private adaptation efforts.

Even though this study has provided interesting insights, there are several limitations. Firstly, we tested only one algorithm for farmers to form income expectations, and predicted income is now an exponential smoothening function of the last N years. However, if a farmer pursues an adaptation option, his predicted income should not be anchored only on past income that was driven by previous choices and conditions. Instead, predictions should be based on expectations about the future probability and severity of droughts and the potential effects of climate change as these processes influence the future gains of drought adaptation. Several other algorithms are available, and it would be interesting to explore the effect of different models for expectation formation in future research.

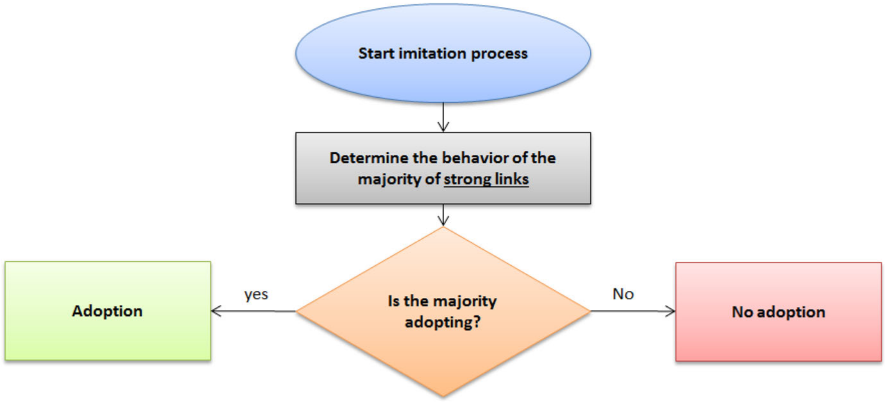
Secondly, in this study crop prices are assumed to be constant. This may not be realistic in cases of large-scale droughts that affect multiple areas in the world. Due to large-scale losses in crop production, commodity prices may increase and farmers' drought loss may be (partially) compensated. Future works should test scenarios for large-scale and small-scale drought through changes in crop prices. Finally, in the Consumat model farmers' decision-making under risk is implemented through an uncertainty ratio that reflects a farmer's risk awareness. However, perceptions of risk are often biased due to risk experience, perceived control or the influence from social networks. Future research to the dynamics of farmers' risk perceptions and its implementation in an ABM is in demand.

Appendix 1: The economic decision model

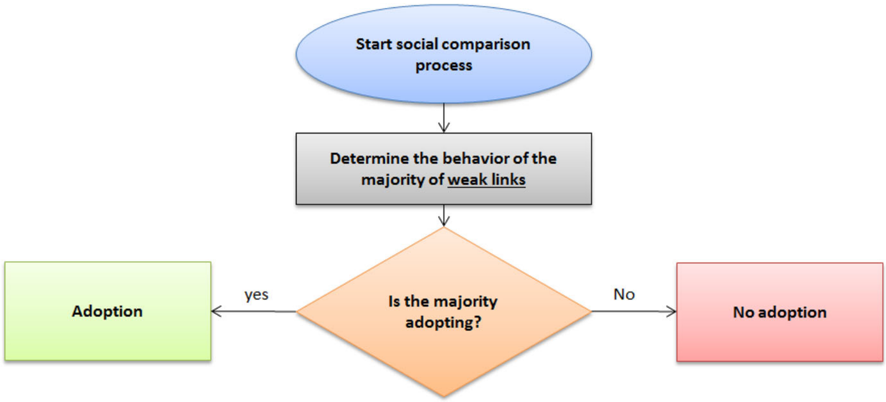


Appendix 2: Decision trees of Consumat strategies

Imitation



Social comparison



Appendix 3: Adaptation strategies

Name	Description	Effect in dry periods	Scale
Optimizing depth and separation of drains	Increasing the depth and spread of drains expands the freshwater lens	Prevents groundwater lenses disappearing and the percolation of salt water	Field
Water-level regulated drainage	The water level in drains is actively increased in summer enlarging the freshwater lens		
Decrease water level in ditches	Water levels in ditches are actively decreased in winter preventing freshwater drainage and enlarging the freshwater lens		
Drain off percolating salt water with a deep drain	Extra deep drain to collect and transport saline groundwater to the ditches, decreasing the percolation pressure		
Freshwater storage in basin	Freshwater storage in a basin	Extra water available for irrigation	
Irrigation	Sprinkler irrigation and drip irrigation	Decreases the crop's exposure to droughts	Farm
Switch to salt-/drought-resistant crops	Switch to salt-/drought-resistant crop varieties or crop types	Decreases the crop's sensitivity to droughts	
Weather insurance	Insurance against financial losses due to catastrophic drought-induced yield failure	Decreases a farmer's financial risk	
Desalinate brackish water	Reverse osmosis technique to desalinate water	Extra water available for irrigation	
Freshwater extraction from creek or sand ridges	Drain to extract freshwater from a water lens in a creek or sand ridge	Extra water available for irrigation	Joint
Freshwater extraction from phreatic aquifers	Well to access freshwater from a phreatic aquifer		
Freshwater injection into deep aquifers	Freshwater storage in a deep aquifer through water injection during wet periods and extraction during dry periods		

References

Ajzen I (2002) Perceived behavioral control, self-efficacy, locus of control and the theory of planned behavior. J Appl Soc Psychol 32:665–683

Arthur WB (1993) On designing economic agents that behave like human agents. J Evol Econ 3:1–22

Arthur WB (1999) Complexity and the economy. Science 2:107–109

Arthur WB (2006) Out of equilibrium economics. Handb Comput Econ 2:1551–1564

Asseng S, Dray A, Perez P, Su X (2010) Rainfall–human–spatial interactions in a salinity-prone agricultural region of the Western Australian wheat-belt. Ecol Model 221:812–824

Aurbacher J, Parker PS, Calberto Sánchez GA, Steinbach J, Reinmuth E, Ingwersen J, Dabbert S (2013) Influence of climate change on short term management of field crops—a modelling approach. Agric Syst 119:44–57

Axtell R (2005) The complexity of exchange. Econ J 115:F193–F210

Balmann A (1997) Farm-based modelling of regional structural change: a cellular automata approach. Eur Rev Agric Econ 24:85–108

Barnes AP, Islam MM, Toma L (2013) Heterogeneity in climate change risk perception amongst dairy farmers: a latent class clustering analysis. Appl Geogr 41:105–115

Batten DF (2001) Complex landscapes of spatial interaction. Ann Reg Sci 35:81–111

Benli B, Kodal S (2003) A non-linear model for farm optimization with adequate and limited water supplies: application to the South-east Anatolian Project (GAP) Region. Agric Water Manag 62:187–203

Berger T (2001) Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. Agric Econ 25:245–260

Berger T, Schreinemachers P (2012) Mathematical programming-based multi-agent systems (MPMAS). Technical model documentation version 3.0. https://www.uni-hohenheim.de/mas/software/Manual.pdf

Berger T, Troost C (2014) Agent-based modelling of climate adaptation and mitigation options in agriculture. J Agric Econ 65:626–348

Boshuizen J, Geurts P, van der Veen A (2009) Regional social networks as conduits for knowledge spillovers: explaining performance of high-tech firms. Tijdschrift voor economische en sociale geografie 2:183–197

Bougheas S, Nieboer J, Sefton M (2013) Risk taking in social settings: group and peer effects. J Econ Behav Organ 92:273–283

Brock WA, Durlauf SN (2005) Social interactions and macro economics. http://www.econ.wisc.edu/archive/wp2005-05.pdf

Brown DG, Riolo R, Robinson DT, North M, Rand W (2005) Spatial process and data model toward integration agent-based models and GIS. J Geograph Syst 7:25–47

Bunn DW, Oliveira FS (2003) Evaluating individual market power in electricity markets via agent-based simulation. Ann Oper Res 121:57–77

Carley KM (2009) Computational modelling for reasoning about the social behaviour of humans. Comput Math Organ Theory 15:47–59

Chen Y, Irwin EG, Jayaprakash C (2011) Incorporating spatial complexity into economic models of land markets and land use change. Agric Resour Econ Rev 40:321–340

Connor JD, Schwabe K, King D, Knapp K (2012) Irrigated agriculture and climate change: the influence of water supply variability and salinity on adaptation. Ecol Econ 77:149–157

Cortignani R, Severini S (2009) Modeling farm-level adoption of deficit irrigation using positive mathematical programming. Agric Water Manag 96:1785–1791

Crooks A (2010) Constructing and implementing an agent-based model of residential segregation through vector GIS. Int J Geogr Inf Sci 24:661–675

Dang HL, Li E, Nuberg I, Bruwer J (2014) Understanding farmers' adaptation intention to climate change: a structural equation modelling study in the Mekong Delta, Vietnam. Environ Sci Policy 41:11–22

Deressa TT, Hassan RM, Ringler C (2011) Perception and adaptation to climate change by farmers in the Nile basin of Ethiopia. J Agric Sci 149:23–31

Durlauf SN, Ioannides YM (2010) Social interactions. Annu Rev Econ 2:451–478

Farmer JD, Foley D (2009) The economy needs agent-based modelling. Nature 460:685–686

Feng L, Li B, Podobnik B, Preis T, Stanley HE (2012) Linking agent-based models and stochastic models of financial markets. Proc Natl Acad Sci USA 109:8388–8393

Filatova T (2014) Empirical agent based land market: integrating adaptive economic behaviour in urban land-use models. Comput Environ Urban Syst. doi:10.1016/j.compenvurbsys.2014.06.007
Filatova T, Voinov A, van der Veen A (2011) Land market mechanisms for preservation of space for coastal ecosystems: an agent-based analysis. Environ Model Softw 26:179–190
García-Vila M, Fereres E (2012) Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. Eur J Agron 36:21–31
Gbetibouo GA (2009) Understanding farmers' perception and adaptations to climate change and variability. International Food Policy Research Institute. http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/31770
Gebrehiwot T, van der Veen A (2015) Farmers prone to drought risk: why some farmers undertake farm-level risk-reduction measures while others not? Environ Manag 55:588–602
Gibbons J, Ramsden S (2008) Integrated modelling of farm adaptation to climate change in East Anglia, UK: scaling and farmer decision making. Agric Ecosyst Environ 127:126–134
Gode K, Sunder S (1993) Allocative efficiency of markets with zero-intelligence traders: market as a partial substitute for individual rationality. J Polit Econ 101:119–137
Graubner M, Balmann A, Sexton RJ (2011) Spatial price discrimination in agricultural product procurement markets: a computational economics approach. Am J Agric Econ 93:949–967
Graveline N, Majone B, van Duinen R, Ansink E (2014) Hydro-economic modeling of water scarcity under global change: an application to the Gállego river basin (Spain). Reg Environ Change 14:119–132
Grimm V, Berger U, Bastiansen F, Eliassen S, Ginot V, Giske J, Goss-Custard J, Grand T, Heinz SK, Huse G, Huth A, Jepsen JU, Jørgensen C, Mooij WM, Müller B, Pe'er G, Piou C, Railsback S, Robbins AM, Robbins MM, Rossmanith E, Rüger N, Strand E, Souissi S, Stillman RA, Vabø R, Visser U, DeAngelis DL (2006) A standard protocol for describing individual-based and agent-based models. Ecol Model 198:115–126
Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF (2010) The ODD protocol: a review and first update. Ecol Model 221:2760–2768
Happe K, Kellermann K, Ballman A (2006) Agent-based analysis of agricultural policies: an illustration of the agricultural policy simulator AgriPoliS, its adaptation and behavior. Ecol Soc 11. http://www.ecologyandsociety.org/vol11/iss1/art49/
IPCC (2014) Climate Change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge
Irwin E (2010) New directions for urban economic models of land use change: incorporating spatial dynamics and heterogeneity. J Reg Sci 50:65–91
Jackson MO (2010) Social and economic networks. Princeton University Press, Princeton, NJ
Jager W (2000) Modelling consumer behavior, Doctoral Thesis. University of Groningen, Universal Press
Jager W, Janssen MA, De Vries HJM, De Greef J, Vlek CAJ (2000) Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model. Ecol Econ 35:357–379
Jager W, Janssen MA (2012) An updated conceptual framework for integrated modeling of human decision making: the Consumat II. In: Paper presented at Workshop Complexity in the Real World @ ECCS 2012—from policy intelligence to intelligent policy. Brussels, 5th & 6th September 2012
Janssen MA, Jager W (1999) An integrated approach to simulating behavioural processes: a case study of the lock-in of consumer patterns. J Artif Soc Soc Simul 2. http://jasss.soc.surrey.ac.uk/2/2/2.html
Janssen S, van Ittersum MK (2007) Assessing farm innovations and responses to policies: a review of bio-economic farm models. Agric Syst 94:622–636
Janssen MA, Jager W (2001) Fashions, habits and changing preferences: simulation of psychological factors affecting market dynamics. J Econ Psychol 22:745–772
Janssen MA, Walker BH, Langridge J, Abel N (2000) An adaptive agent model for analysing co-evolution of management and policies in a complex rangeland system. Ecol Model 131:249–268
Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47:263–291
Kasperson RE, Renn O, Slovic P, Brown HS, Emel J, Goble R, Kasperson JX, Ratick S (1988) The social amplification of risk: a conceptual framework. Risk Anal 8:177–187
Kirman A (2006) Heterogeneity in economics. J Econ Interact Coord 1:89–117
Kirman A, Vriend NJ (2001) Evolving market structure: an ACE model of price dispersion and loyalty. J Econ Dyn Control 25:459–502
LeBaron B (2001) Evolution and time horizons in an agent-based stock market. Macroecon Dyn 5:225–254

Leclère D, Jayet PA, de Noblet-Ducoudré N (2013) Farm-level autonomous adaptation of European agricultural supply to climate change. Ecol Econ 87:1–14
Liu J, Dietz T, Carpenter SR, Folke C, Alberti M, Redman CL, Schneider SH, Ostrom E, Pell AN, Lubscenco J, Taylor WW, Ouyang Z, Deadman P, Kratz T, Provencher W (2007) Coupled human and natural systems. AMBIO J Hum Environ 36:639–649
Lux T (2009) Rational forecasts or social opinion dynamics? Identification of interaction effects in a business climate survey. J Econ Behav Organ 72:638–655
Maddux JE, Rogers RW (1983) Protection motivation and self-efficacy: a revised theory of fear appeals and attitude change. J Exp Soc Psychol 19:469–479
Magliocca N, Safirova E, McConell V, Walls M (2011) An economic agent-based model of coupled housing and land markets (CHALMS). Comput Environ Urban Syst 35:183–191
Mandleni B, Anim FDK (2011) Climate change awareness and decision on adaptation measures by livestock farmers in South Africa. J Agric Sci 3:258–268
Maneta MP, Torres MO, Wallender WW, Vosti S, Howit R, Rodrigues L, Bassoi LH, Panday S (2009) A spatially distributed hydroeconomic model to assess the effects of drought on land use, farm profits, and agricultural employment. Water Resour Res. doi:10.1029/2008WR007534
Manski CF (2000) Economic analysis of social interactions. National Bureau of Economic Research, Working Paper 7580. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.111.6138&rep=rep1&type=pdf
Manson SM, Jordan NR, Nelson KC, Brummel RF (2014) Modeling the effect of social networks on adoption of multifunctional agriculture. Environ Modell Softw. doi:10.1016/j.envsoft.2014.09.015
Mansury Y, Gulyás L (2007) The emergence of Zipf's Law in a system of cities: an agent-based simulation approach. J Econ Dyn Control 31:2438–2460
McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: homophily in social networks. Annu Rev Soc 27:415–444
Mens M, van der Sluijs J, ter Maat J, Jeuken A (under review) Analysing the robustness of an agricultural drought risk sysmte: a case in a coastal polder area in the Netherlands. Water Resour Manag
Miahle F, Becu N, Gunnell Y (2012) An agent based model for analysing land use dynamics in response to farmer behaviour and environmental change in the Pampanga delta (Philippines). Agric Ecosyst Environ 161:55–69
Ministerie van Economische Zaken Landbouw en Innovatie (2011) Deltaprogramma 2012, Werk aan de Delta, Maatregelen van nu, voorbereiding voor morgen
Ministerie van Verkeer en Waterstaat (2010) Deltaprogramma 2011. Werk aan de Delta, Investeren in een veilig en aantrekkelijk Nederland nu en morgen. https://www.rijksoverheid.nl/documenten/jaarplannen/
Mulde HM, Veldhuizen AA (2014) AGRICOM 2.01 manual. Alterra 21, Wageningen **(in Dutch)**
Müller B, Bohn F, Dreßler G, Groeneveld J, Klassert C, Martin R, Schluter M, Schulze J, Weise H, Schwarz N (2013) Describing human decisions in agent-based models—ODD + D, an extension of the ODD protocol. Environ Model Softw 48:37–48
Natalini D, Bravo G (2014) Encouraging sustainable transport choices in American households' results from an empirically grounded agent-based model. Sustainability 6:50–69
Nolan J, Parker D, van Kooten GC, Berger T (2009) An overview of computational modeling in agricultural and resource economics. Can J Agric Econ 57:417–429
Parker DC (2014) Chapter 16: an economic perspective on agent-based models of land use and land cover change. In: The Oxford handbook of land economics. Oxford University Press, New York
Parker DC, Brown DG, Filatova T, Riolo R, Robinson DT, Sun S (2012) Do land markets matter? A modelling ontology and experimental design to test the effects of land markets for an agent-based model of ex-urban residential land-use change. In: Agent-based models of geographical systems. Springer, Berlin
Robinson DT, Brown DG (2007) Evaluating the effects of land-use development policies on ex-urban forest cover: an integrated agent-based GIS approach. Int J Geogr Inf Sci 23:1211–1232
Robinson DT, Brown DG, Parker DC, Schreinemachers P, Janssen MA, Huigen M, Wittmer H, Gotts N, Promburom P, Irwin E, Berger T, Gatzweiler F, Barnaud C (2007) Comparison of empirical methods for building agent-based models in land use science. J Land Use Sci 2:31–55
Rogers RW (1975) A protection motivation theory of fear appeals and attitude change. J Psychol 91:93–114
Rogers EM (2003) Diffusion of innovations, 5th edn. Free Press, New York

Schreinemachers P, Berger T, Sirijinda A, Praneetvatakul S (2009) The diffusion of Greenhouse Agriculture in Northern Thailand: combining econometrics and agent-based modeling. Can J Agric Econ 57:513–536

Schreinemachers P, Potchanasin C, Berger T, Roygrong S (2010) Agent-based modeling for ex-ante assessment of tree crop innovations: litchis in Northern Thailand. Agric Econ 2010:519–536

Simon HA (1997) Models of bounded rationality: empirically grounded economic reason, vol 3. Massachusetts Institute of Technology, Cambridge, MA

Slovic P (1987) Perception of risk. Science 236:280–285

Slovic P, Finucane ML, Peters E, MacGregor DG (2004) Risk as analysis and risk as feelings: some thoughts about affect, reason, risk and rationality. Risk Anal 24:311–322

Slovic P, Finucane ML, Peters E, MacGregor DG (2007) The affect heuristic. Eur J Oper Res 177:1333–1352

Sopha BM, Klöckner CA, Hertwich EG (2013) Adoption and diffusion of heating systems in Norway: coupling agent-based modeling with empirical research. Environ Innov Soc Transit 8:42–61

Speelman EN (2014) Gaming and simulation to explore resilience of contested agricultural landscapes. Wageningen University, ISBN 9789461739049

Sun Z, Müller D (2013) A framework for modeling payments for ecosystem services with agent-based models, Bayesian belief networks and opinion dynamics models. Environ Model Softw 45:15–28

Sun J, Tesfatsion L (2007) Dynamic testing of wholesale power market designs: an open-source agents-based framework. Comput Econ 30:291–327

Tang J, Folmer H, Xue J (2013) Estimation of awareness and perception of water scarcity among farmers in the Guanzhong Plan, China, by means of a structural equation model. J Environ Manag 126:55–62

Tesfatsion L (2002) Agent-based computational economics: growing economies from the bottom up. Artif Life 8:55–82

Tesfatsion L, Judd LT (2006) Agent-based computational economics: a constructive approach to economic theory. Handb Comput Econ 2:831–880

Toft HI, O'Hanlon PW (1979) A dynamic programming model for on-farm decision making in a drought. Rev Mark Agric Econ 47:5–16

Tolk L (2012) Zoetwater verheldert: Maatregelen voor zoetwater zelfvoorzienendheid in beeld. Kennis voor Klimaat. http://edepot.wur.nl/258933

Troost C, Berger T (2014) Dealing with uncertainty in agent-based simulation: farm-level modeling of adaptation to climate change in Southwest Germany

Tversky A, Kahneman D (1973) Availability a heuristic for judging frequency and probability. Cogn Psychol 5:207–232

Tversky A, Kahneman D (1992) Advances in prospect theory: cumulative representation of uncertainty. J Risk Uncertain 5:297–323

Van den Hurk B et al (2006) KNMI Climate Change Scenarios 2006 for the Netherlands. 35 KNMI, De Bilt, Utrecht

van Duinen R, Filatova T, Geurts P, van der Veen A (2014a) Empirical analysis of farmers' drought risk perception: objective factors, personal circumstances, and social influence. Risk Anal. doi:10.1111/risa.12299

van Duinen R, Filatova T, Geurts P, van der Veen A (2014b) Coping with drought risk: empirical analysis of farmers' drought adaptation in the south-west Netherlands. Reg Environ Change. doi:10.1007/s10113-014-0692-y

van Oel PR, Krol MS, Hoekstra AY, Taddei RR (2010) Feedback mechanisms between water availability and water use in a semi-arid river basin: a spatially explicit multi-agent simulation approach. Environ Model Softw 25:433–443

van Oel PR, Krol MS, Hoekstra AY (2012) Application of multi-agent simulation to evaluate the influence of reservoir operation strategies on the distribution of water availability in the semi-arid Jaguaribe basin, Brazil. Phys Chem the Earth Parts A/B/C 47–48:173–181

Von Neumann J, Morgenstern O (1944) Theory of games and economic behavior. Princeton University Press, Princeton, NJ

Wheeler S, Zuo A, Bjornlund H (2013) Farmers' climate change beliefs and adaptation strategies for a water scarce future in Australia. Glob Environ Change 23:537–547

Wilensky U (1999) NetLogo, Center for connected learning and computer-based modeling. Northwestern University, Evanston, IL. http://ccl.northwestern.edu/netlogo/

Wossen T, Berger T, Mequaninte T, Alamirew B (2013) Social network effects on the adoption of sustainable natural resource management practices in Ethiopia. Int J Sustain Dev World Ecol 20:477–483